Observed Shape Detection from EEG Time Series

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Abstract— **Brain computer interface studies required recording of a physiological response of a subject to exhibit relevant information. This extracted information can be used to perform an action and the amount of the information plays a significant role in the determination of brain computer interface (BCI) performance. The use of improved experimental paradigms as well as measuring the brain responses using electroencephalogram (EEG) is the most common approach for the BCI studies. In this study, the classification of the ongoing brain activity occurring as response to the four shapes is managed and reported. We applied Fourier transform to obtain the frequency spectrum regarding the one second time series of each channel with a time overlap of 50% to the feature set of each stimulus type. Four machine learning classifiers are implemented, and in the concept of the classification, (delta, theta, alpha, beta, and gamma) band power values for one second period constituted the feature set, resulting in a total of 315 features. Among the four ML classifier Quadratic Discriminant 87.1% recorded the highest accuracy.**

Keywords— ***electroencephalogram, shape detection, classification, machine learning***

I. INTRODUCTION

In the last decades, researchers have been trying to understand the electrophysiological output of the brain under the presence of several stimuli. Among the stimulus types, visual one is the most common. The visual system analyzes the visual image by breaking it down into basic characteristics such as color, shape, motion, depth, and texture. Studying each of these attributes should be devoted to humans, dedicated neurons, and unique visual regions. The identification of the visual stimulus plays a significant role in the knowledge extraction process for the brain-computer interface (BCI) studies.

The BCI is a multidisciplinary research field comprising neuroscience, computerized signal processing, and machine learning. Mind percussion comprehension is the prime focus in BCI. A brain computer interface (BCI) is a sophisticated technique for creating an immediate correspondence between a human brain [1] and a Machine BCI solution which are most effective and widely applicable are those based on noninvasive EEG measurements obtained from the scalp. The study begins by identifying as well as decoding brain signals to learn more about how the brain functions and reacts to certain activities, such as monitoring a video or just observing some scenes or doing some physical task. These rhythms are micro-electrical activities that are generated in our brain while we do some mental tasks. The most common and cost-effective noninvasive technique for recording such brain rhythms is called electroencephalogram (EEG) signals. Moreover, EEG has the highest temporal resolution property, which enables the extraction of several features in both the temporal and frequency domain [2]. By the use of Machine Learning (ML) methods, we can distinguish and classify the responses measured by EEG in the presence of different visual stimuli.

Preparing models from different exploratory states can be used to prepare ML classifiers, and it can estimate the ability to reliably and strongly differentiate new models. ML can become the most important factor and attempts to identify the data with algorithms and predict something that a human mind may imply. In our study, we focus on the classification of the EEG brain signals taken from individuals while watching four different shapes (cone, cube, cylinder, and sphere) presented on a computer screen using an EEG device and applying Fourier transform for the feature extraction and machine learning for the classification.

Quite a few cognitive neuroscience studies [3], [4], [5] have explored those parts of the visual cortex and brain that are responsible for certain cognitive processes, but no specific solution has been found so far. This course focuses on the complexities of computational approaches focused on perception to perform visual tasks.

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II. Related work

Research into visual scene analysis [6] was first motivated by a convincing [7] concept. He postulated that the visual system's function was to give an impersonation of what exhibit in our universe. Nevertheless, the experience of observing complicated scenes is almost unchallenging and happens quickly, with highly nuanced and diverse sensory inputs. Activating a wide Cascading of various brain areas requires just a few hundred milliseconds, each transforming the sensory input differently [8].

A study for distinguishing object shapes from EEG signals as well as tactile signals acquired from a capacitive tactile sensor while viewing objects of various shapes [9] thus establishing a mutually beneficial relationship or dependence for haptic information between these two sources in response to the same tactile stimuli. The Emotiv EEG Head and the PPS Tactile Sensor were used to collect experimental data, while subjects with closed eyes dynamically explored objects of ten various shapes. autoregressive parameters were used for the extracted EEG data as well as for the tactile datasets and KNN with 3 neighbors were used for the classification of feature spaces obtained from both EEG data and tactile senser. The mean accuracy for the classification of EEG signal is 74.21% and for the tactile is 97.12%.

A study performed a shape-analog letter perception in which subjects observed four letters (i.e. 'p', 'q', 'b', and 'd') while EEG signals was recording to evaluate the feasibility of classification and classification effectiveness of shape-analog letters utilizing EEG signals [10]. The discriminative power of each feature was determined using the F-score methodology, and then a subset of high-discriminative power features was fed into the classifier. Five ML classifiers K-nearest neighbor (KNN), Support Vector Classifier (SVC), Linear Discriminant Analysis (LDA), Random Forest (RF), and AdaBoost (ADA) was used to identify brain activity in shape analogous letter perception. Among the mentioned classifiers RF had a maximum accuracy of 74.1%, though, it was not statistically significantly better than the SVC. regarding the performance comparison among the classifiers.

Using simple different shapes induces cognitive load and it has an effect on EEG signals. Annovative approach for classification of EEG signals from different brain regions of visual cognitive load using analytical wavelet transformation (AWT) [11]. For the classification SVM and ensemble subspace, KNN was used. And the characteristic vector dimension is reduced by using SVM Classifier after the implementation of Principal Component Analysis (PCA). Both quadratic and cubic kernels were used in that work. ESKNN classifier had the highest accuracy among other classifiers 86.12% which is 86.12% higher than SVM and KNN classifiers.

Exploring the potentiality of monitoring BCI by analyzing visual perception (VP) and visual imagery (VI) [12]. Four subjects participated in the study and their stimuli consisted of six different colored shapes. researchers performed a time-frequency analysis, using event-related spectral perturbation ERSP and the OpenBMI tools. Both signals were filtered and segmented for the classification of VP and VI. For the classification of data CNN network with two layers for both six-class classification in VP and binary classification for VP and VI were used. The accuracy results for both were 32.56% and 90.16%. Their findings suggest that each class of VP can be classified as well as VP and VI can be classified from the brain signals. since they demonstrated excellent performance, particularly with binary classification.

A study to examine the (object/animal) recognition utilizing dense EEG data presented in [13]. The experiment included 9 healthy participants asked for designation of the displayed image at a normal speed 148 when appears on a screen. A statical t-test analysis was performed in the study for the ERP. when averaging the signals of all subjects it shows that it follows the same behaviors but when analyzing all channels without averaging it shows high activation in the bilateral occipital lobe for both categories but the animal higher than the object. For the classification of the two categories, a support vector machine was applied and SVM indicated good productivity and assure it's possible to separate the two classes' animals and objects with an average accuracy of 82.70%.

III. Method

A. Data Acquisition

We recorded the brain signals of ten subjects while watching four different shapes (cone, cubic, cylinder, and sphere) presented on a computer screen. The four shapes were presented randomly for four seconds. The subjects were asked to do nothing just to observe the shapes on the screen. Fig. 1, summarizes our system design.

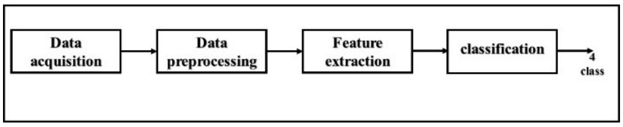

Fig. 1. the experimental design.

B. Data Preprocessing and EEG Feature Extraction

The preprocessing of EEG signals is about ameliorative the signal noise to ratio (SNR). Noise generated by the participant, outside effects, or electrodes is cleaned from the raw signals to display relevant information. For the preprocessing phase, we used Brain Products Analyzer software to remove the noise and the artifacts from the EEG signals. The measurement above 100 microvolts is discarded from further analysis as in [14].

The EEG signals were used for further processing and evaporation of the features. A feature is a performance evaluation attribute of the process being studied, and any EEG activity reported includes the various features. EEG raw data signals do not provide valuable information on their own, hence requiring specific signal processing to extract relevant information found within the signal. Selecting an effective method for analyzing the signal is an important step when extracting information from EEG data. Generally speaking, no single approach can produce the best results. Therefore, many methods need to be tested. For example, the choice of signal analysis tool depends on the features of the signal and the intent of the study. Features can be directly obtained from the raw signals and from the transformations or raw signal compositions, for example, utilizing techniques such Fourier transform, wavelet, Short-time Fourier transform, Empirical mode decomposition, etc. In our study, using MATLAB, we obtained the frequency spectrum for one-second time series of the five frequency bands power delta (0-4) HZ, theta (4-8) HZ, Alpha (8-13) HZ, Beta (13-30) HZ, and gamma (30-45) HZ, correspondingly, from low to high frequency with a 50% time overlap for the feature extraction phase. In addition, we labeled the feature set regarding the four shapes (1-cone, 2-cube, 3-cylinder, and 4-sphere). In the concept of the classification, the five-frequency band-power values (delta, theta, alpha, beta and gamma) of each one second period constituted the feature set with 500Hz sampling rate x 63 channels yielding 315 features were used for the Machine learning classification.

C. *Classification of EEG Features*

The classification phase of the EEG signals included the implementation of Machine Learning classifiers for the extracted features. Having a simple and well-defined method which produces results is very useful. Even though machine learning (ML), and artificial intelligence (AI) are used synonymously, ML is a subfield of AI. ML comprise the utilizing of algorithm or procedure by AI to learn from the data. ML learning phase consists of two stages, assessment of unknown system constraints from a given dataset, and utilization of estimates Dependence on predicting new machine outputs [15]. Machine learning can be supervised learning, unsupervised learning and semi-supervised learning which is a combination of supervised and unsupervised learning. In our study the learning algorithm is supervised learning where a machine is assigned certain inputs and the expected outputs. the machine then attempts to create a correlation between the parameters and outputs. The purpose of the relationship developed by supervised learning is to forecast the outcomes for a series of inputs that were not included in learning. There are two main approaches in the supervised learning classification and regression. Our supervised learning was multi class classification in which we had four class for our presented shapes. In our study, four ML learning included for classification; SVM, KNN, ensemble subspace KNN, and quadratic discriminant classifier.

Support vector machine (SVM), supervised learning method works with linear and nonlinear data and can handle classification problems as well as regression issues. SVM is typically a binary classifier that is concentrated on structural risk minimization. In complex nonlinear computing, the SVM routes the training samples into a high dimensional feature domain where a linear hyperplane will isolate the data. In nonlinear complicated simulations, the SVM assigns the data points to a higher dimensional space where the data can be divided by a linear hyperplane. The SVM training process aims to define the linear function to differentiate the data. SVMs are a part of the general kernel system group [16]. The productivity of SVMs depends heavily on the selection of kernels, but it is very difficult to choose the kernel functions that are well suitable for the particular problem. A kernel method is a technique that relies heavily on the data only through dot-products. The dot product may be replaced by a kernel function, which computes a dot product in such probably high-dimensional application domain. Previously, the SVM was designed to solve binary classification problems, but the method was then enhanced to deal with multi-class. In contrast, the "one vs. one" technique is more effective than other methods in scenarios with more classes., Moreover a possible unbalance nature of the dataset, does not cause any problems [17]. Linear, quadratic, and cubic kernels are introduced for SVM.

K-nearest neighbor (KNN) method is a lazy, simple supervised machine learning model that can be utilized to resolve both regression and classification tasks. Of all ML techniques, KNN model is one of the least complex. The theory of majority vote is used to determine class labels taking into account the weightings of distances [18]. The classifier for KNN is the base for many lazy learning algorithms. It essentially stores the entire training set and delay all attempts to generalize inductively until the time of classification. KNN makes assumptions by retrieving the least (most similar) distant k instances of a given query and predicting its weighted majority class as the query class. During the training process, certain stored values are required. This algorithm is based on the approximation of the nearest neighbor. The new cases are categorized based on the measure of similarity which is the metric distance. The distance measure is most widely used. KNN classifier weakness is the long duration that is needed to locate the nearest neighbors in a broad training set [19]. The KNN classifier's operation can be summed up as follow, Compute the distance between the signal point and the point in the sample dataset for the known category attribute and then, Set the distance in increasing order and choose the k spots that are closest to the present position. In the present study, one nearest neighbor is implemented (k=1) with an equally weighted Euclidean distance metric for fine k-nearest neighbor. 315 characteristics are subjected to the classifier without any extraction process being implemented.

Ensemble classification based primarily on the concept founding principle. An ensemble's generalization ability is usually much powerful than a single learner. Ensemble learning which aims to enhance the efficiency of a binary model by combining multiple comparative classifiers demonstrates its adaptability and generalization effectiveness [20]. More precisely, Ensemble learning can be further split into the form of boosting, and bagging which is by far the most representative method [21]. The procedure of ensemble learning starts by adding the second-best classifier with a first best classifier, and then the ensemble is formed by driving the third best classifier and evaluating the performance, repeating this process for all classifiers. The ensemble is developed in a two-stage by assessing the models using two distinct performance metrics, misclassification rate and Brier score[22]. In our study, we implemented Ensemble Subspace KNN employing the same sets of features obtained from EEG measures. In the classification process we used all features with 30 learner setting as the nearest neighbors for the scalp dataset. And the subspace dimension was 158, where we've included all of the classification features.

Quadratic discriminant analysis (QDA), a standard probabilistic classification method that is used to separate estimates of at least two groups of objects or events by a quadric surface. Quadratic discriminant functions induce a nonlinear boundary of class decisions. the QDA generates a matrix of covariance for each class, which has more efficient parameters than LDA. The quadratic classifier with a total covariance structure is applied separately in the present study.

IV. RESULTS

In this section, we applied the machine learning classifier for the extracted feature from the conventional frequency bands and we performed the evaluation of the performance. We adopted fivefold cross-validation for EEG measurement regarding the four shapes (1-cone, 2-cube, 3-cylinder, and 4-sephere). The classifiers' mean accuracy values were calculated and reported. Table I, summarizes the accuracy results of each classifier. Quadratic Discriminant had the highest accuracy among the other classifiers with a value of 87.1% accuracy. It is followed by Fine KNN (82.9% accuracy) for one neighbor (k=1), Ensemble Subspace KNN (81% accuracy) with 30 learners, and the lowest accuracy was recorded with Cubic SVM as 75.4 %.

EEG scalp images from the brain electrical time series for the four shapes with band power are shown in fig. 2, fig. 3, fig. 4, and fig. 5 respectively as labeled (cone, cube, cylinder, and sphere).

TABLE I. CLASSIFICATION ACUURACY RESULTS FOR THE FOUR SHAPES (CONE, CUBE, CYLINDER, AND SPHERE).

classifiers	**cone**	**Cube**	**Cylinder**	**Sphere**	**Average accuracy**
Quadratic Discriminant	85.5%	88.1%	84.5%	90.4%	87.1%
K-nearest neighbor	84.7%	80.6%	83.1%	83%	82.9%
Ensemble	83.1%	78.9%	82.3%	79.4%	81%
Support vector machine	79.9%	72.6%	72.9%	75.9%	75.4 %

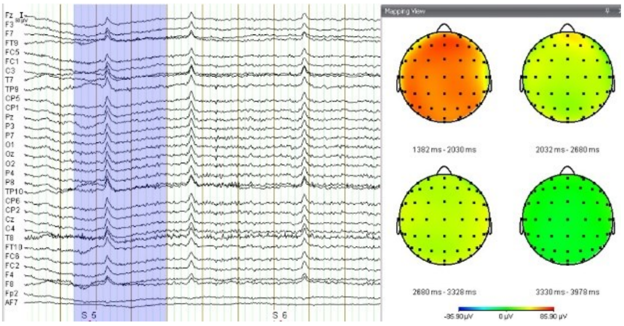

Fig. 2. EEG scalp image of the brain time series for the cone shape.

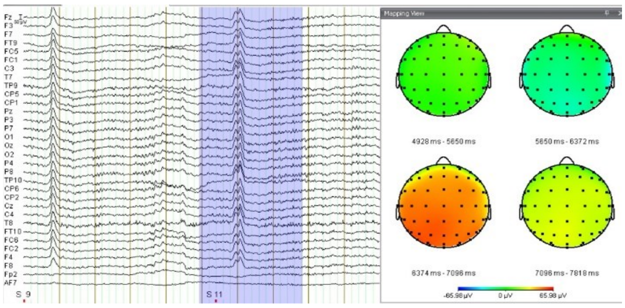

Fig. 3. EEG scalp image of the brain time series for the cube shape.

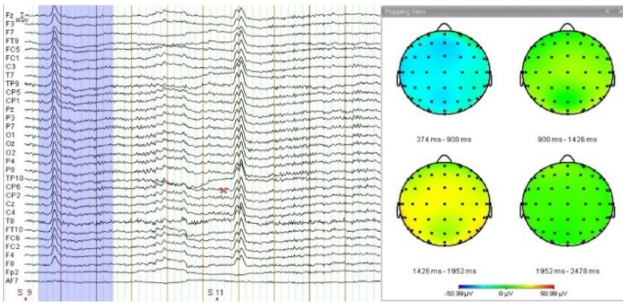

Fig. 4. EEG scalp image of the brain time series for the cylinder shape.

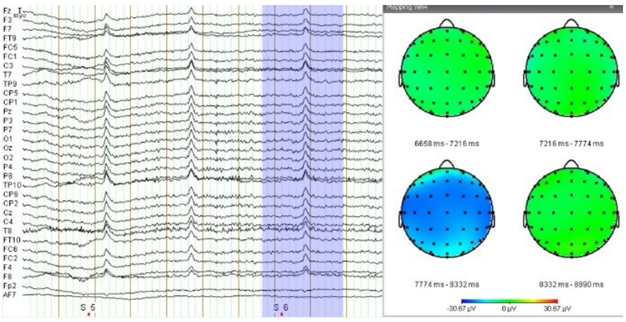

Fig. 5. EEG scalp image of the brain time series for the sphere shape.

V. DISCUSSION

Ventral stream is a pathway from the primary visual cortex to the temporal lobe, carrying visual information. According to one commonly accepted theory, the ventral stream (so named because of the direction that it takes along the ventral side of the brain) carries knowledge about the shape and perception of objects. The ventral stream within the brain, particularly the cortex of the inferior temporal visual association, have an important function in recognizing the shape and objects we receive. When we have met a visual cue, the scalp electrodes will assess our brain responses in milliseconds. The objectives of this study were to distinguish between EEG brain responses related to various shapes. As a result, rather of employing ERP measurements, we concentrated on the continuous EEG responses. Problems of object detection and identification in biological vision have been studied extensively, and in recent years object recognition has become a key focus of computer vision and artificial intelligence. If we have viewed a visual cue, the scalp electrodes will record our brain responses in milliseconds. In our study, we classify the brain signals for ten individuals watching four different 2D shapes (cone, cube, cylinder, and sphere). We defined conventional frequency band-power values close to those of the measured EEG signal [23] during the stimulus-watching period.

In the classification of four shapes, we trained four ML learners the Quadratic Discriminant had the highest accuracy 87.1% followed by KNN 82.7%. In conclusion, cone, cube, cylinder, and sphere are defined in the definition of this study using EEG data of one-second duration. As for future work, more complex shapes and objects or complex scenes will be classified. Moreover, sophisticated techniques like deep learning can be adopted for the classification problem of EEG measured concerning shape stimuli. Deep learning was used to discriminate the event-related potentials using the scalp topographies in two classes [24]. For our study, a similar approach can be formulated to identify the stimulus class based on topographies deduced from short-length multi variate EEG time series.

Our results using ML methods still remain promising as a short length time series used for input and the time taken for the classification seems to be reasonable. Hence, machine learning has great potential to advance the neuroscience field, not as a substitute for hypothesis-driven analysis, but in combination with it. Machine learning development methods will satisfy the great promise they carry with suitable replication, evaluation, and hypothesis driven evidence, assessing us in larger progress for determining how the brain functions.

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